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Analytic Medical Process for Ophthalmic Pathologies Using Fuzzy C-Mean Algorithm

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ABSTRACT

Traditionally, the diagnoses of diseases are carried out by medical experts with professional experience on clinical data of patients and adequate knowledge of identifying diseases. However, such diagnosis is found to be approximate and time-consuming. It's also purely depends on the availability and experience of the medical experts dealing with imprecise and uncertain data. An enhanced approach is considered to mitigate the time consuming nature of disease diagnoses. Several simulated diagnosing system has been developed, but most of these diagnosis system are design to possess the clinical data and symptoms associated with a specific disease as knowledge base. The quality of the knowledge base has an impact not only on the consequences, but also on the diagnostic precision. Most of the existing systems have an expert system that contains all diagnoses facts as rules. Specifically, applying the concept of a **Fuzzy Set** have proven better knowledge representation to improve analytic medical process. Hence, this research work attempt to design and develop such diagnosis system, using **Fuzzy C- Means Algorithm.** The ophthalmic pathological results obtained from Fuzzy C Means approach shows faster and reliably good clustering. The system developed was evaluated using simple clustered symptoms that are added to clinical data to determine the status of **Glaucoma** and its severity.

Keywords: Knowledge Base, Ophthalmic Pathologies, Fuzzy Set, Fuzzy C-Means, Glaucoma,

1. INTRODUCTION

Ophthalmic pathology is the sub-specialty of pathology and ophthalmology that focuses on diseases of the eye (glaucoma) and its neighboring tissues. Glaucoma is a disease which affects the eye and causes blindness. It is an ophthalmologist disease characterized by an increase in intraocular pressure (IOP). Early detection of the disease will help prevent against developing a more serious condition. There are two types of glaucoma namely open angle and closed angle. In open angle glaucoma the patient may not feel any symptoms, whereas closed angle glaucoma the patients may get the pain and vision loss. The treatment of glaucoma is either by the application of eye drop or surgery, it will not suitable for all patients because, they cannot tolerate the pain (Narasimhan & Vijayarekha, (2011); (Anjana *et al.*, 2012). Glaucoma is not a curable disease which losses the vision of the eye and cannot be restored.

There are various factors to be considered for diagnosing the glaucoma such as inner eye pressure, the shape and color of the optic nerve, complete field of vision and angle in the eye where the iris meets the cornea, thickness of the cornea etc. The symptoms depend on the type and extent of the disease and may include; sudden eye pain, headache, redness of the eye, vomiting, blurred vision and vision rainbow. Although the number of the people affected by primary open angle glaucoma varies in different reports, it is estimated that there will be 60.5 million people with glaucoma worldwide by 2010 increasing to 79.6 million people in 2020 Quigley & Broman (2006). One of the most prevalent forms is primary open angle glaucoma (POAG) accounting for up to 74.0% of all glaucoma Quigley & Broman (2006). POAG has a serious impact on the quality of life of a large number of people around the world Alward (2000). Glaucoma is the second most common cause of blindness after cataract in Nigeria and approximately 980 000 Nigerians are blind due to it (Abdul et al., 2009). Glaucoma is a slowly progressive disease and because it presents with few noticeable symptoms, about half of affected individuals are unaware that they have the disease (Tielsh et al., 2000).

Glaucoma in Africans may present late, with up to 50% of cases already blind in one eye at presentation Cook (2009). Under normal circumstances people should seek treatment early in the course of the disease so as to prevent further vision loss as well as to preserve the quality of life (Gasch, Wang & Pasquale 2000). However, the motivation to do so seem to be most likely related to the knowledge of glaucoma risk factors, signs and symptoms and an understanding of the natural history of the disease. There are various existing clinical ophthalmic instruments like Heidelberg retina tomography (HRT) and optical coherence tomography (OCT) that provides colorless 3-d visualization. An early diagnosis of glaucoma will increase patients' survival rate. The design of an effective diagnosis model is therefore an important issue in glaucoma diagnosis.

Fuzzy logic provides a means for representing and manipulating data that are not precise, but rather fuzzy. Fuzzy logic presents an inference morphology that enables appropriate human reasoning capabilities to be applied to knowledge-based systems. The theory of fuzzy logic encompasses a mathematical strength to capture the uncertainties associated with human cognitive processes. This research work will develop and implement an automated approach for the diagnosis and give possible recommendation of glaucoma using Fuzzy C Means clustering technique for high precision and reliable clinician supervision. FCM clustering algorithm is being used as the problem solving and reasoning algorithm in the inference engine of the knowledge base system for the evaluation, classification and matching of patterns to more than one class of glaucoma.

1.1. Statement of the Problem

Problems with glaucoma patients are not easily discovered in an early stage as it will be functioning normally even when it is partially damaged. An early diagnosis of glaucoma will increase patients' survival rate. The combination of non-specific clinical manifestations that characterize ophthalmic pathologies (glaucoma) and lack of reliable expertise, lost of patients information and adequate experience among ophthalmologist exponentially increases the potential for misdiagnosis of glaucoma.

In a conventional computer diagnostics system, symptoms of glaucoma are obtained using Boolean logic reasoning of yes/no, this is not really how a medical doctor reasons, ophthalmologist reasons approximately by deciding the degree of present of a symptoms in a patient, example, redness of eye could be mild/low or severe/high. Based on this fuzzy logic that employs approximate reasoning as vague, imprecise and noisy data is found appropriate for diagnosing glaucoma. Some of the symptoms look alike and so are to be clustered for easy processing.

2. REVIEW OF RELATED LITERATURE

Mei-lang Huang et al (2007) used an automated classifier based on adaptive neuro-fuzzy inference to differentiate between normal and glaucoma eyes from he quantitative assessment of summary data reports of OCT in Taian Chinese population. With Stratus OCT parameters used as input, the results from neuron fuzzy shoed promising results for discriminating between glaucomatous and normal eyes with 90% accuracy.

Rajendra Acharya et al (2011) developed a glaucoma diagnosis system using a combination of texture and higher order spectral features with a random forest classifier and achieved an accuracy of 91%.S. Sekhar et al. (2008) The proposed technique as tested on the DRIVE database of retinal images this consists of 40 fundus images of dimensions 768x584. Captured by a canon CR5 non-mydriatic 3CCD camera ith a 45o field of view (FOV). These images contain both normal (healthy) and abnormal retinas. In his study, 36 of these images were used (4 images have been excluded for not having visually-detectable optic disks). The performance of the optic disk localization as evaluated based on the determined optic disk location with regard to an expert. Proposed method is capable of localizing the optic disk correctly for 34 of these images (success rate of 94.4%). Method is able to detect the fovea in all of these 34 images with a success rate.

K. Kavitha et al (2014) proposed a glaucoma screening for optic disc and opic cup segmentation for the area under curve (AUC) of the ROC curves by various cup segmentation methods. Therefore, the AUC significantly larger than IOP, threshold, r-bend. ASM, and regression methods. The results show smaller CDR errors in CDR measurement and higher AUC in glaucoma screening by the proposed method. The proposed disc and cup segmentation methods achieve an AUC of 0.800.0.039 lower than AUC of 0.839 of the manual CDR computed from Manuel disc and Manuel cup. In the results for the SCES dataset, the proposed method achieves AUC 0.822 in the screening SCES data, which is much higher than 0.660 by the currently used IOP measurement discussions with clinicians, the accuracy is good enough for a large-scale glaucoma.

Chalinee Burana-Anusorn et al.(2010) proposed a method to calculate the CDR automatically from fundus images. The optic disc is extracted using an edge detection approach and a variation level-set approach individually. The optic cup is then segmented using a color component analysis method and threshold level-set method. After obtaining the contours, an ellipse fitting step is introduced to smoothen the obtained results, the performance of this approach is evaluated using the proximity of the calculated CDR to the manually graded CDR. The results evaluated using the proximity of the calculated CDR to the manually graded CDR. The results indicate that our approach provides 89% accuracy in glaucoma analysis. As a result, this study has a good prospective in automated screening systems for the early detection of glaucoma. Subi. P. P. (2014). proposed super pixel classification based methods for disc and cup segmentations for glaucoma screening and an approach to the quick detection and extraction of macula from the images of human retina.

In disc segmentation, HIST and CSS balance each other. CSS due to distinguish variations. Reliability score is an important indicator of the automated results. In this research, disc segmentation, because the color change from cup to Neurorentinal rim is much smaller. Therefore, the uneven illumination becomes a large noise affecting the cup segmentation. The CSS computed rom the centre surround difference is less sensitive. It is important to point out that the proposed super pixel classification is used as an initialization for deformable models. Macula segmentation is of paramount importance in developing automated diagnosis expert system for doctors.

Wong et al (2009) applied a level set method to the region within the optic disc for the detection of the optic cup, here accurate segmentation Is more difficult due to the denser vascular architecture ithon the optic disc. An alternate method using histogram based analysis of the color pixel intensity is also employed for optic cup segmentation. Smoothing of the cup contours detected through these methods is similarly performed using direct ellipse fitting. CDR values calculated are fused with the help of support vector machine (SVM).Zhuo Zhang et al (2009) proposed a fused approach based on multimodalities including level set segmentation, convex hull and ellipse fitting boundary smoothing for optic cup detection. Optimized vertical cup height calculated using intensity and level set based approach is smoothed using convex hull. Nevertheless, this work adopted fuzzy C-means algorithm for the development of analytic medical process to detect glaucoma and provide possible prevention of ophthalmic pathological disease. The approach seems to provide high order spectral related features classifier and is required to achieve more than 91% operational precision.

3. SYSTEMS ANALYSIS AND ALGORITHMIC SPECIFICATION

3.1 Analysis of the Existing System

On arrival at the eye center/hospital, the patient is required to register and get an identification code for subsequent diagnosis. The completed registration form is stored in a file cabinet and contains personal information about the patient. This information is used to maintain a record of patient and trace her health history in the hospital. The patient is subjected to a manual observation by the doctor, during which the doctor ask key questions to ascertain the existence of glaucoma. The doctor takes decision based on his/her experience in the field. There is no unified model for decision making which impedes the quality of decision made. Decisions made manually by the doctors are error prone and these calls for a computerized diagnoses system for glaucoma using a well know fuzzy c-means algorithm.

3.1.1 Architecture of the Existing

The conceptual architecture of that show the manual way of diagnosing Glaucoma disease is shown in Fig 1;

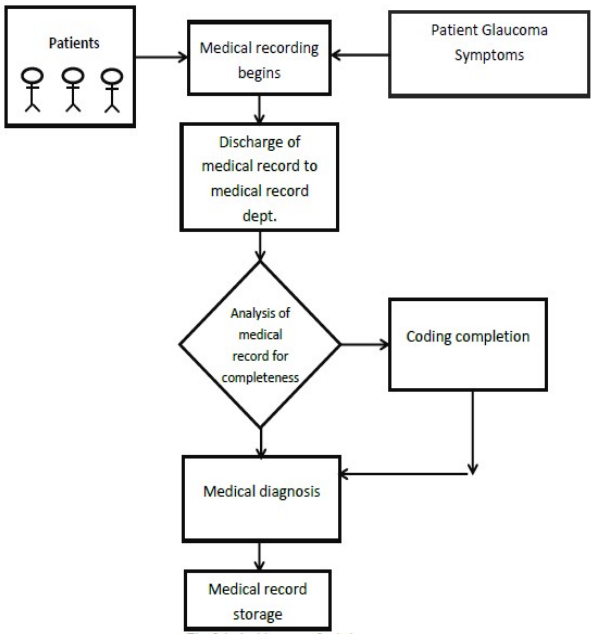

Fig. 1: Architecture of existing system

3.2 Proposed System Design

In this project work, we propose a fuzzy c-means algorithm for the diagnosis of Glaucoma disease. To visualize the overall system, the conceptual architecture of the system is presented in section 3.2.1;

3.2.1 Architecture of the Proposed System

An architecture description is a formal description and representation of a system, organized in a way that supports reasoning about the structures and behaviors of the system. It shows the various components of the system and how they interact with each other. The Architecture of the proposed analytic medical process for ophthalmic pathologies based on Fuzzy C-Means Algorithm is illustrated in figure 2.

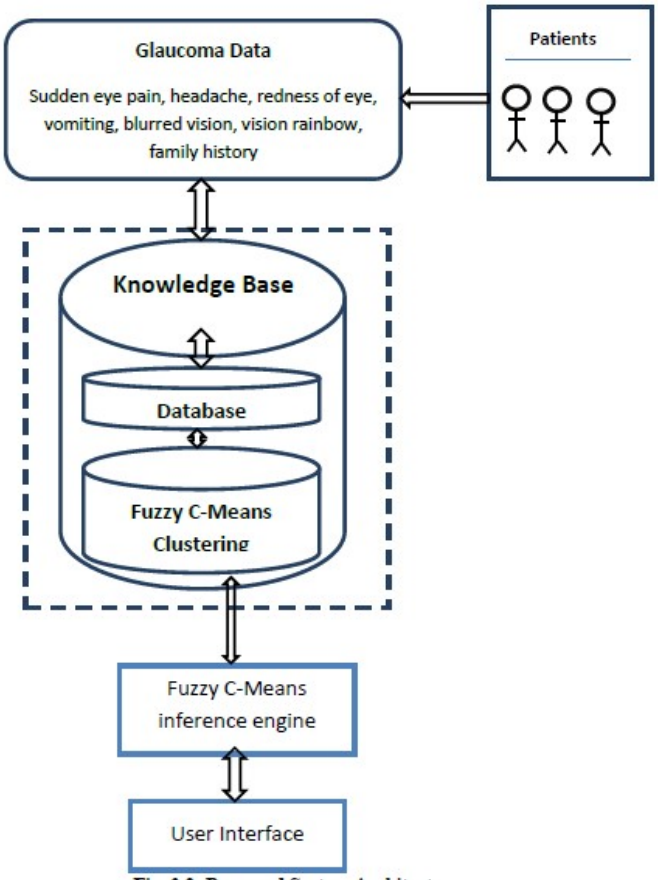

Fig. 2: Proposed System Architecture

3.2.2 Description of the Key Component

The key components of this system are described below;

1. **Glaucoma Data:** This represents all the data used in the diagnosis of a patient. These data includes sudden eye pain, headache, redness of eye, vomiting, blurred vision, vision rainbow. These data forms the symptoms used by our system.
2. **Fuzzy C-Means Inference Engine:** This component of the system does inference about the data supplied to the system. It carries out the inference using fuzzy rules.
3. **Knowledge Base:** The function of a knowledge base is to store knowledge. In our system knowledge is stored as a set of production rules.

4. **Database:** This is a database management system that holds patient's information, patients diagnose results etc. In this research work, the MySQL database management system is used.
5. **Fuzzy C-means Algorithm:** This is a component that provides the implementation of the C-means algorithm. This component uses the java programming language to implement and expose the functionality of this algorithm to the Diagnosis module. This module is implemented using the Matlab programming language.
6. **User Interface:** User interface (or Graphical User Interface) is used to view and save the result of diagnosis.

3.3 Design Algorithms

The algorithm employed in this work is the Fuzzy C-mean algorithm. This algorithm is presented below;

```
// K is initial number of clusters, Imax is the iteration of fuzzy
// c-means, p is for the weight
Input: initial number of clusters K, Imax, p
------------step 1: -------------
//initialize weights of prototype
for k = 0 to K-1
        for q = 0 to Q-1 w[q,k] = random();
------------step 2: -------------
//standardize the initial weight over K
for q = 0 to Q-1
        sum = 0.0;
        for k = 0 to K-1
                sum = sum + w[q,k];
        for k = 0 to K-1
                w[q,k] = w[q,k] /sum;
                ****************************************
// starting fuzzy c-means loop
I = 0
------------step 3: -------------
// standardize cluster weights over Q
for k = 0 to K-1
        min = 99999.0; max =0.0;
        for q = 0 to Q-1
                if (w[q,k] > max)
                        max = w[q,k];
                if (w[q,k] < min)
                        min = w[q,k];
        sum = 0.0
        for q = 0 to Q-1
                sum = sum + (w[q,k] – min) /( max –min);
        for q = 0 to Q-1
                w[q,k] = w[q,k]/sum;
------------step 4: -------------
// compute new prototype center
for k = 0 to K-1
        for n = 0 to N-1
```

```
                sum = 0.0;
                for q = 0 to Q-1
                        sum = sum + w[q,k] x[n,q];
                z[n,k] = sum;
        ------------step 5: -------------
// compute new weight
for q = 0 to Q-1
        sum = 0.0
        for k = 0 to K-1
                D[q,k] =0.0;
                        for n = 0 to N-1
                                D[q,k] = D[q,k] + (x[n,q] – z[n,k])2
                        sum = sum + (1/(1 + D[q,k]))1/(p-1) ;
                for k = 0 to K-1
                        W[q,k] = (1/(1 + D[q,k]))1/(p-1) /sum;
------------step 6: -------------
I = I + 1
If I < Imax
        Goto step 3;
// end of fuzzy c-means loop
```

3.4 Model Formulation

This project work considers **Fuzzy C-Means Algorithm**, the following model is used;

The fuzzy c-means (FCM) algorithm is an iterative algorithm that generalizes the hard c-means algorithm to allow any point partially belongs to multiple clusters (Kumar, Verma, & Shrma 2010). The aim of FCM is to find clusters centers that minimize a dissimilarity function and then partition a finite collection of elements, $X=\{x_1, x_2, x_3 \ldots x_n\}$, into a collection of fuzzy clusters, $C=\{c_1, c_2, \ldots, c_p\}$ with respect to some given criterion (Ekong, Onibere & Imianvan, 2011). The algorithm is implemented in the following steps (Kumar et al.,2010)

Set m,c, and ε, such that $m > 1$, $2 \le c < n$, and $0 < \varepsilon < 1$

i. Initialize $U=[u_{ij}]$ Matrix, U(0) (1)

ii. At k-step: calculate the centre vectors
C(k)=$[c_{ij}]$ with U(k)

$$C_j = \frac{\sum_{i=1}^{n} u_{ij}^m x_i}{\sum_{i=1}^{n} u_{ij}^m} \quad (2)$$

iii. Update U(k) , U(k+1)

$$u_{ij} = \sum_{k=1}^{p} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{-2}{m-1}} \quad . \quad . \quad (3)$$

with the following constraints :

$0 \le u_{ij} < 1, \quad \forall i, j$

$$\sum_{j=1}^{p} u_{ij} = 1, \qquad \forall i \tag{4}$$

v. if ||U(k+1) - U(k)|| < ε then STOP: otherwise return to step (iii)

where,

U - partition matrix

u_{ij} - degree of membership of x_i in the cluster j

x_i - the ith of d-dimensional measured data

c_j w - the d-dimension center of the cluster

ε - termination criterion

k - maximum number of iteration steps

m - the fuzzification parameter

p - the number of clusters

d - the dimension of the dataset

i. Objective Function: In each iteration of the Fuzzy C-means algorithm, the following objective function is minimized; as shown in equation (5)

$$J = \sum_{i=1}^{N} \sum_{j=1}^{C} \delta_{ij} \parallel x_i - c_j \parallel^2 \tag{5}$$

Here, N is the number of data points, C is the number of clusters required, c_j is the centre vector for cluster j, and δ_{ij} is the degree of membership for the ith data point x_i in cluster j. The norm, $\| x_i - c_j \|$ measures the similarity (or closeness) of the data point x_i to the centre vector c_j of cluster j.

ii. **Degree of membership:** For a given data point x_i, the degree of its membership to cluster j is calculated as follows;

$$\delta_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \tag{6}$$

Where, m is the fuzziness coefficient and the center vector c_j is calculated as follows;

$$c_j = \frac{\sum_{i=1}^{N} \delta_{ij}^m . x_i}{\sum_{i=1}^{N} \delta_{ij}^m} \tag{7}$$

Where m is the called the fuzziness coefficient and is bounded by [1 ∞].

3.5 Model Implementation

The fuzzy C-means algorithm is implemented in java. Some of the java functions used in the implementation of this system as presented below;

1. Calculate Objective Function ***(OF ())***;
2. Calculate Cluster Centers From ***MFs ()***;
3. Calculate MFs From Cluster Centers (***CC***()));
4. Calculate Distance ***(float[ ] a1, float[ ] a2)***

4. SYSTEM DESIGN

A system is a set of interacting parts, created for some particular purpose. Core activities in system design include developing system-level technical requirements and top-level system designs and assessing the design's ability to meet the system requirements. In this section - database design, system block diagram, and system flow diagram are design.Realistic medical field data from patients used for analytical processing for system implementation is as shown inTtable 1

Table 1: Medical field data of patients

Patient No	SEP	HD	RE	VO	BV	VR	FH	Defuzzified output(0-1)
P01	M	L	L	M	M	L	H	0.5
P02	H	H	M	M	H	H	H	0.9
P03	M	H	H	L	M	M	M	0.9
P04	L	M	M	L	M	H	L	0.6
P05	H	H	H	L	M	H	H	0.8
P06	M	L	H	L	M	H	M	0.6
P07	H	M	H	M	M	M	M	0.5
P08	H	M	M	L	M	M	M	0.7
P09	L	L	L	L	M	H	M	0.4
P10	M	H	M	L	H	H	L	0.9
P11	M	H	L	M	H	M	M	0.8
P12	H	H	M	M	M	H	H	0.9
P13	H	H	H	H	M	M	H	0.9
P14	H	M	L	M	M	L	M	0.9
P15	M	H	H	L	L	M	H	0.8
P16	M	H	H	L	L	M	M	0.7
P17	L	L	M	M	L	M	M	0.6
P18	L	M	H	L	M	H	H	0.3
P19	M	M	L	L	L	M	M	0.2
P20	H	M	M	L	L	H	H	0.4

4.1.1 Fuzzy Linguistics Variables

The linguistic variables defined for this system represents each of the patient's symptoms. These variables, their description and their ranges of values (called the universe of discourse) are presented in Table 2.

Table 2: Fuzzy Linguistics Variables

S/N	VARIABLE	DESCRIPTION	UNIVERSE OF DISCOURSE (%)
1	SEP	Sudden eye pain	0-1
2	HD	Headache	0-10
3	RE	Redness of the eye	0-100
4	VO	Vomiting	0-1
5	BV	Blurred vision	0-1
6	VR	Vision rainbow	0-10
7	FH	Family History of glaucoma	0-100

4.1.2 Definition of Fuzzy Clusters

In this system, four (4) clusters are used. These clusters include AACG, SACG, POAG, and STG. Each patient will be classified to each cluster with varying degree of membership. The definition of fuzzy cluster is presented in Table 3.

Table 3: Fuzzy Cluster

S/N	CLUSTERS	VARIABLES	DESCRPTION
1	Cluster 1	AACG	Acute Angle Closure Glaucoma
2	Cluster 2	SACG	Secondary angle closure
3	Cluster 3	POAG	Primary open angle
4	Cluster 4	STG	Steroid induced glaucoma

4.1.3 The RULE BASE

A rule base stores the rules used in this system. The type of rules used in this system is called production rule. These rules have to part – the rule antecedent (IF part) and the rule consequent (ELSE part). The rule base of the system used in implementation is indicated in Table 4.3. The Table indicates that : L = Low, M = Moderate, and H = High.

Table 4. The System Rule Base

RULE NO.	SEP	HD	RE	VO	BV	VR	FH	CLUSTER
Rule 1	L	L	L	L	L	L	L	SACG
Rule 2	H	L	L	L	M	H	L	SACG
Rule 3	H	H	H	L	H	M	H	AACG
Rule 4	M	H	H	M	H	M	H	AACG
Rule 5	L	M	M	L	H	H	M	POAG
Rule 6	H	M	H	L	H	L	M	POAG
Rule 7	M	H	M	L	H	H	M	POAG
Rule 8	M	H	M	M	M	M	M	POAG
Rule 9	H	H	H	L	H	H	H	STG
Rule 10	L	L	M	L	H	M	L	POAG
Rule 11	M	H	M	L	L	H	H	AACG
Rule 12	H	H	M	M	H	H	H	AACG
Rule 13	H	H	L	L	H	M	M	POAG
Rule 14	H	M	L	M	M	M	h	AACG

4.1.4 Membership Function Values

The type of membership function used in this work is the triangular membership function. This membership function is defined by three parameters – *left, center and right*. Matlab programming tool is used to implement the membership function as shown in Table 5.

Table 5: Membership Function (MF)

LINGUISTICS VARIABLE	INPUT FUNCTION VALUES		
	Low	Moderate	High
SEP	[0, 0, 0.4]	[0.1, 0.5, 0.9]	[0.6, 1, 1.4]
HD	[0, 0, 4]	[1, 5, 9]	[6, 10, 14]
RE	[0, 0, 40]	[10, 50, 90]	[60 100 140]
VO	[0, 0, 0.4]	[0.1,0.5, 0.9]	[0.6, 1, 1.4]
BV	[0, 0, 0.4]	[0.1, 0.5, 0.9]	[0.6, 1, 1.4]
VR	[0, 0, 4]	[1, 5, 9]	[6, 10, 14]
FH	[0, 0 39.7]	[10, 50, 90]	[60, 100, 140]
OUTPUT FUNCTION VALUES			
GLAUCOMA	[0, 0, 0.4]	[0.1, 0.5, 0.9]	[0.6, 1, 1.4]

4.1.5 Membership Function Plot

The Graphical Representation of the plots of Membership Functions using Matlab tools is as illustrated in the figures that follows

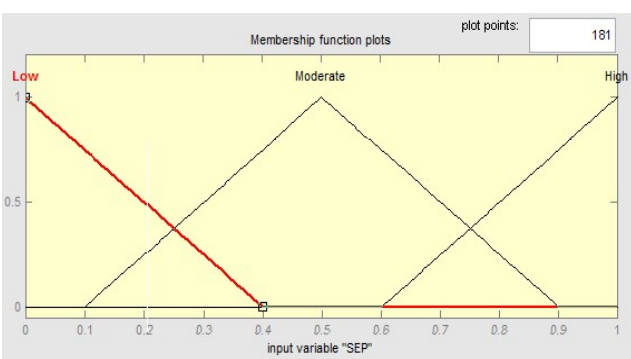

Fig 3: Membership function plot for Sudden Eye Pain

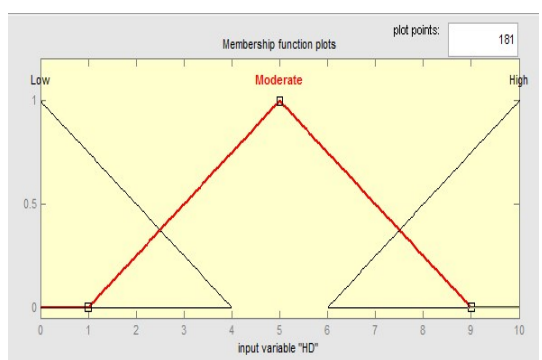

Fig 4: Membership function plot for headache

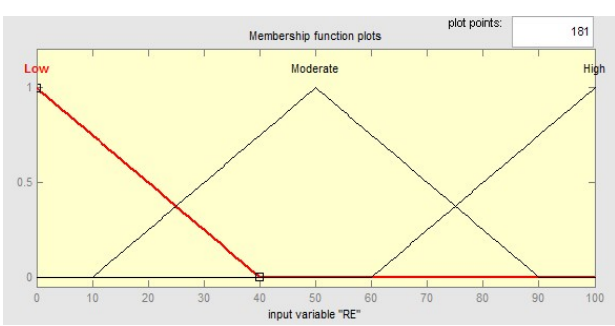

Fig 5: Membership function plot for Redness of the eye

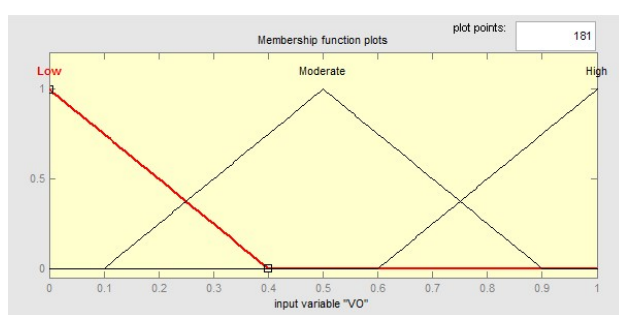

Fig 6: Membership function plot for vomiting

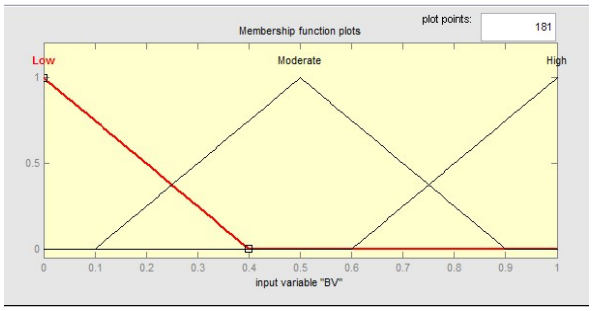

Fig 7: Membership function plot for blurred vision

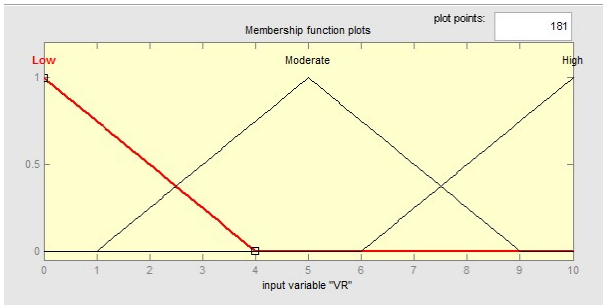

Fig 8: Membership function plot for vision rainbow

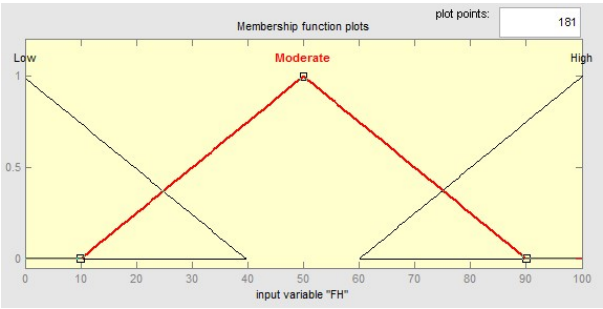

Fig 9: Membership function plot for family history

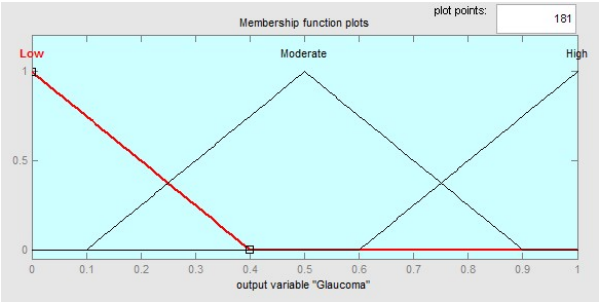

Fig 10: Membership function plot for Glaucoma history

Database Design

This is the description of database tables used by the system. These tables include – patient's profile table, report table, and admin table. The design and descriptions of these tables are shown below;

4.2.1 Patient's Profile Table

This database table stores patient's profile information. These information includes patient's ID, patient's name, address, gender etc. This table is presented in table 4.2.

Table 6: Patient's Profile Table

S/N	FIELDNAME	DATA TYPE	SIZE
1	Patient_ID (PK)	Varchar	8
2	Patient_name	Varchar	45
3	Address	Varchar	30
4	Phone	Number	11
5	Gender	Varchar	6
6	Next_of_kin	Varchar	45

Patient's Profile form is represented in figure 112 below

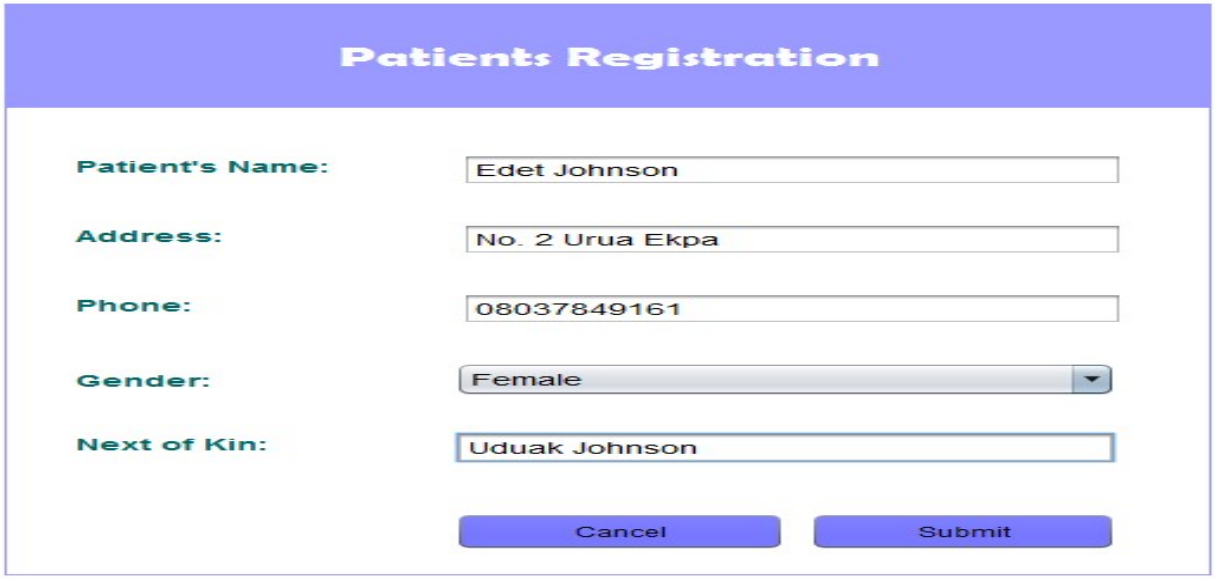

Fig. 112: Patient's Profile Form

4.3 Report Table

This table stores patient's diagnosis results which can be viewed later.

Table 7: Report Table

S/N	FIELDNAME	DATA TYPE	SIZE
1	Patient's_ID	Varchar	8
2	Patient's_name	Varchar	45
3	Degree_of_low	Number	4
4	Degree_of_moderate	Number	4
5	Degree_of_high	Number	4

Patient's Diagnosis Results is represented in figure 4.3 below

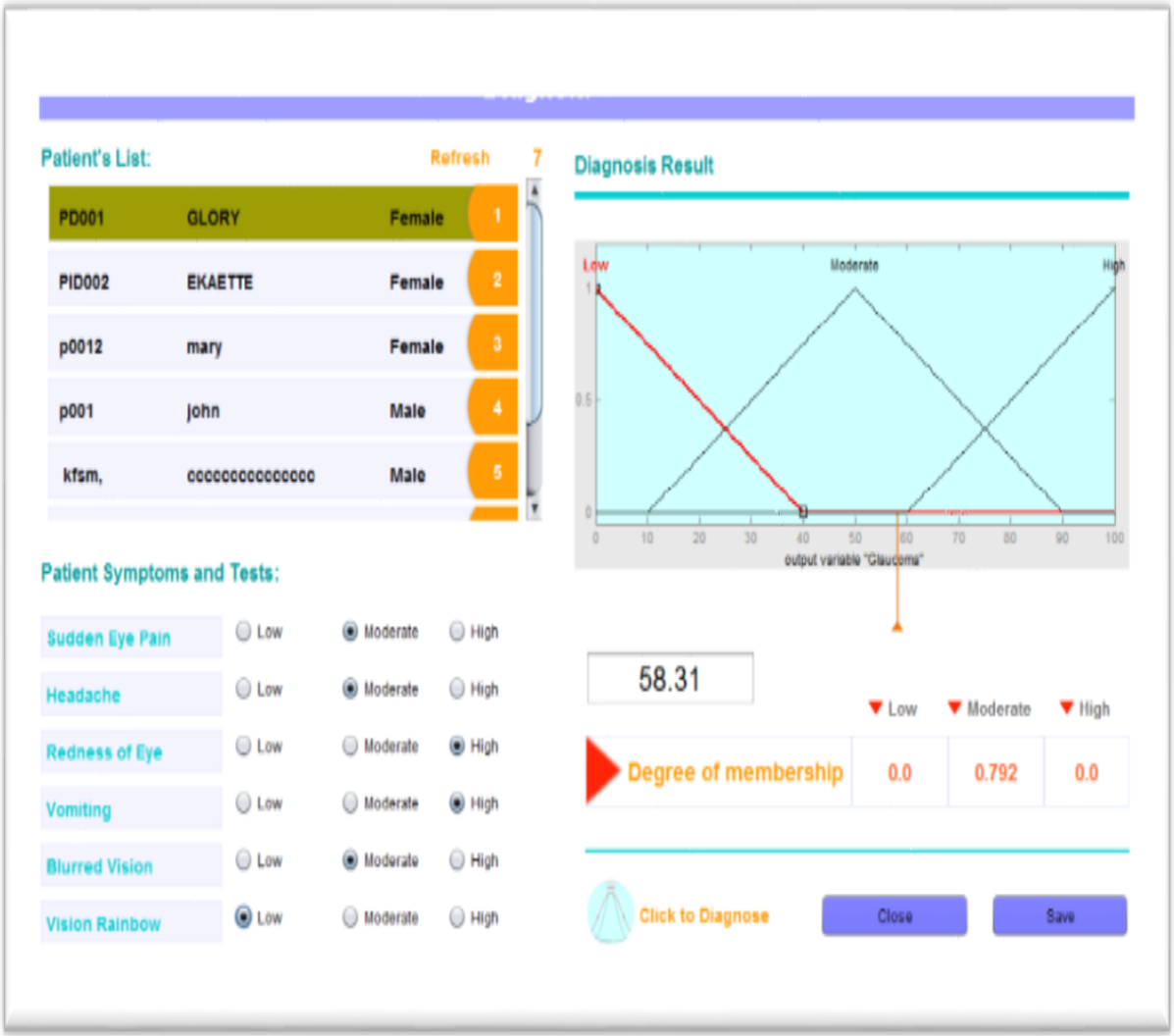

Fig. 12: Patient's Diagnosis Results

4.4 Evaluation/ Discussion of Results

The results obtained from the system showed degree of glaucoma in a typical patient diagnosed. The degrees are given in terms of values such as: **0.1-100 LOW, 0.1-100 MODERATE, 0.1-100 HIGH**. The case study results are given in **crisps** that are not fuzzified, thereby making it difficult to determine the extent to which a patient suffers from the illness. The medical expert (ophthalmologist) may not reliably expressed the medical details of degree of glaucoma in most patient he consulted for on the severity of the illness. The proposed system classifies the degree of mildness (low), modesty (moderate) and severity (high) in term of numbers (value) realistically as **70% severity, 20% modesty, 10% mildness.**

From the results seen in table 4.0 patient No. 9, 18, 19, 20 patient has only 0.4,0.3, 0.2 and 0.4 degree of glaucoma, this is considered low whereas patient no 2, 3, 9, 12, 13 each has 0.9 degree, this is considered very high, in the existing system all these patients are reported to have glaucoma and possibly would have be administered the same therapy, This shows that therapy have been abused, that is a situation when a patient with low glaucoma is administered same therapy as a patient with high glaucoma. Practically, the research findings of the proposed system seek to address the anomalies by employing **Fuzzy C-Means** which demonstrated analytic medical details with degrees of certainties

5. CONCLUSION

In spite of the constant advancement in the field of medical sciences, diagnosis of eye disease remains a challenging task. Glaucoma is not easily discovered at its initial stage, early diagnosis of this is therefore highly important. As a part of the ongoing efforts to make diagnosis more effective, this study accordingly developed a fuzzy cluster means system to support the diagnosis of glaucoma using a set of clinical signs and symptoms. Our model allows for the classification of and matching of cluster groups to glaucoma symptoms. The experimental results show that the proposed model can improve the quality of glaucoma diagnostics.

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